

*R-S AND S(-O)-R: ALTERNATIVE
DESIGNS FOR NEURAL NETWORKS*

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Donahoe, Palmer, and Burgos continue to press their excellent case for neural network modeling as a part of behavior analysis. They suggest, but do not say, that the analogies between connectionist architectures and the traditions of associationism and S-O-R psychology, as well as notions such as the strengthening of stimulus-response bonds, are a necessary evil, due to the need to rely upon the biological basis of long-term potentiation (LTP). Activationist neural networks, currently under development in our laboratory,¹ rely upon the biological basis of in vitro reinforcement (IVR) (Stein, this issue; Stein, Xue, & Belluzzi, 1993, 1994)² and have few if any analogies to any sort of associationism. These facts underlie the present commentary.

Of two initial reactions noted here, the first concerns dialogue: Although Donahoe, Burgos, and Palmer (1993) analyzed the data of Stein et al. (1993) substantially differently than the original authors did themselves, Donahoe et al. (this issue, pp. 196–197) make that difference entirely clear, prompting an important dialogue to be joined (Stein, this issue).

The second issue concerns terminology. Donahoe et al. (1993, as well as Donahoe &

Palmer, 1994) speak of their models as “selectionist,” and yet the structure of the networks they propose appears to follow an S-R logic (or to use the terminology they prefer, an S-O-R logic), rather than an R-S logic, as seems dictated by the term *selectionist*. The simulations presented by Donahoe et al. (pp. 207–208) provide eloquent replies to such concerns, replies I will address here.

The S-R Issue

Donahoe et al. refer to this second issue as the S-R issue. The Cartesian tradition of explaining behavior in terms of *automata* encompasses both the S-R and S-O-R approaches in 20th century psychology, but not the R-S approach. Donahoe et al. go to great lengths to distance themselves from S-R psychology, but admit to a “distant relation” (p. 203) between connectionist neural networks, including their own selection neural network, and S-O-R psychology. The present commentary will concern itself only with aspects of Donahoe et al.’s approach that are compatible with *both* the S-R and S-O-R views. To avoid terminological confusion, this generalized approach will be called S(-O)-R in the present discussion.

The S(-O)-R approach entails certain assumptions. These include: (a) ultimately, stimuli are causal antecedents of responses, (b) some sort of pathway leads from the sense organs to the motor effectors enabling this causal relation, (c) these pathways can differ in efficiency, and (d) reinforcement strengthens environment-behavior relations by altering the efficiencies of these pathways.

Traditionally, theorists committed to the S(-O)-R approach have expressed behavioral laws in terms of control by antecedents. Skinner, taking an R-S approach, tended to express behavioral laws in terms of control by consequences. Donahoe et al. are correct to point out that the distinction between approaches is “at the level of behavior, not at

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¹ Kemp, S. M., & Eckerman, D. A. (1995, November). *The art of shaping and the shaping of art: Search in Hamming space using an IVR-based neural network*. Poster session presented at the annual meeting of the South Eastern Association for Behavior Analysis, Charleston, SC.

² Stein, L. (1995, May). *Skinner’s behavioral atom: A cellular analogue of operant conditioning and its implications*. Paper presented at the annual meeting of the Association for Behavior Analysis, Washington, DC.

the level of biological mechanism" (p. 196). But it is equally clear that Donahoe et al.'s own research demonstrates that it is now possible to contrast various explanatory approaches in terms of neural network models at the level of the underlying physiology as well as at the level of behavioral laws.

Donahoe et al. claim that R-S behavioral laws are "implemented by changes in synaptic efficacies" (p. 196). This claim fits in well within the purview of the generalized S(-O)-R approach. But an alternative is possible: It may be that control by consequences at the behavioral level is implemented by changes in neural firing rates (IVR) rather than synaptic efficiencies (LTP).

Neural networks allow investigations of both the R-S and S(-O)-R approaches at both levels of analysis, that of behavioral law and that of biological mechanism. Donahoe et al.'s approach is R-S at the level of behavioral law and S(-O)-R at the level of biological mechanism. Relying upon the biobehavioral constraints of the evidence of IVR, Kemp and Eckerman (see Footnote 1) have proposed a neural network that is pure R-S at both levels. In short, connectionist neural networks are, as Donahoe et al. claim, "suitable to interpret operant behavior," despite the analogy between LTP and the S-R approach (p. 194). Activationist neural networks, which incorporate R-S logic at a microstructural level, may be more suitable.

Because, as Donahoe et al. correctly point out, "behavior does not fully constrain biology" (p. 197), neither behavioral data nor neurophysiological data alone will resolve the issue. Only a combined effort in behavioral, neurophysiological, and computational science will do.

An Alternative: Piano-Forte

Long-term potentiation is evidence for a theory about neural plasticity that is caused by changes in synaptic efficiencies. Connectionist neural networks model learning by simulating changes in synaptic efficiencies using changes in connection weights. In vitro reinforcement (Stein, this issue; Stein et al., 1993; see also Footnote 2) is evidence for a theory about neural plasticity that is caused by changes in neural firing rates. A new type of neural network, called an activationist neural network, models this conception of learning by simu-

lating changes in neural firing rates using changes in the units' activation functions.

Kemp and Eckerman have constructed an activationist neural network called Clavier (see Footnote 1), whose design is biobehaviorally constrained by IVR rather than by LTP. Clavier is designed to continuously emit responses quite independently of any sensory input. The distribution of responses is shaped solely by the history of reinforcement. The effect of reinforcement is not to strengthen the environmental control of responding but simply to strengthen responding. Clavier is designed to be shaped to any arbitrarily selected response topography using the percentile reinforcement schedule (Platt, 1973).

An expanded R-S network, called Piano-Forte, is under development to model Skinner's three-term contingency without relying on changes in connection strength. Sensory inputs serve solely in what has been called a *modulatory* capacity (Rescorla, 1991). That is, discriminative stimuli have their causal effect, not upon responses but upon the relation between responses and reinforcement.

In Piano-Forte, discriminative stimuli never *increase* the probability of appropriate responses at all, but only *decrease* the probability of inappropriate responses (i.e., focus attention). Modeled at a neurophysiological level, discriminative stimuli have no excitatory effects whatsoever. Discriminative stimuli determine which responses are strengthened by allowing some behavioral atoms (Stein et al., 1994; see also Footnote 2) to emit responses (and thus to be subject to reinforcement) and not others.

Comparing the Models

Donahoe et al. have taken the first step in developing computational techniques for evaluating a neural network model with respect to the S-R issue (pp. 207-208). Their diagnostic as to whether or not a model is of the S(-O)-R variety is to shut down afferent inputs to the computer simulation of the model and then look to see if the model continues to perform any useful or interesting functions.

For traditional neural network models, shutting off afferent inputs brings the system to an immediate halt, because in such models, all responses are elicited. Such networks model the doctrine "no response without a stimulus" (Skinner, 1979, p. 143). Clavier is

designed to learn entirely without afferent inputs. It is pure R-S. Donahoe et al.'s selection neural network gives intermediate results: Responses continue to be produced, but conditioning does not occur.

Conclusion

Obviously, we do not know whether the brain is "wired up" according to Donahoe et al.'s (1993) blueprint or according to some R-S blueprint, as suggested above. If history is any guide, the next generation of behavior analysts, far better informed about neurophysiology and neuroanatomy than we can hope to be, will find that the answer is "both and neither." For the present, however, Donahoe et al. (1993, as well as Donahoe & Palmer, 1994) have done great service in introducing the notion of a selectionist neural network into the behavior-analytic repertoire. As with any new line of research, the wider the initial variation among the approaches taken, the better able the scientific contingencies will be to select the most fruitful avenues.

I look forward to head-to-head comparisons of the performance of all the various selectionist neural networks with real animal data from the laboratory (Kemp & Eckerman, 1995).³ As a final point, I would em-

phasize that neural network simulations can serve no purpose in behavior analysis except to adjudicate between alternative accounts of actual behavior. Donahoe et al. have started us on the road to being able to make such judgments. I applaud their efforts and their successes.

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³ Kemp, S. M., & Eckerman, D. A. (1995, May). *Direct analysis of contingencies using working models*. Paper presented at the annual meeting of the Association for Behavior Analysis, Washington, DC.